Taylor & Francis
Taylor & Francis Group

Production Planning & Control
The Management of Operations

ISSN: 0953-7287 (Print) 1366-5871 (Online) Journal homepage: http://www.tandfonline.com/loi/tppc20

Factors influencing user acceptance of public sector big open data

Vishanth Weerakkody, Kawaljeet Kapoor, Maria Elisavet Balta, Zahir Irani & Yogesh K. Dwivedi

To cite this article: Vishanth Weerakkody, Kawaljeet Kapoor, Maria Elisavet Balta, Zahir Irani & Yogesh K. Dwivedi (2017) Factors influencing user acceptance of public sector big open data, Production Planning & Control, 28:11-12, 891-905, DOI: 10.1080/09537287.2017.1336802

To link to this article: https://doi.org/10.1080/09537287.2017.1336802

Published online: 11 Jul 2017.

PRODUCTION PLANNING & CONTROL, 2017
VOL. 28, NOS. 11–12, 891–905
https://doi.org/10.1080/09537287.2017.1336802

Taylor & Francis
Taylor & Francis Group

OPEN ACCESS Check for updates

Factors influencing user acceptance of public sector big open data

Vishanth Weerakkody[a], Kawaljeet Kapoor[b], Maria Elisavet Balta[c], Zahir Irani[a] and Yogesh K. Dwivedi[d]

[a]Faculty of Management and Law, University of Bradford, Bradford, UK; [b]Business School, Brunel University, Uxbridge, UK; [c]Kent Business School, The University of Kent, Canterbury, UK; [d]School of Management, Swansea University, Swansea, UK

ABSTRACT
In recent years Government departments and public/private organisations are becoming increasingly transparent with their data to establish the whole new paradigm of *big open data*. Increasing research interest arises from the claimed usability of big open data in improving public sector reforms, facilitating innovation, improving supplier and distribution networks and creating resilient supply chains that help improve the efficiency of public services. Despite the advantages of big open data for supply chain and operations management, there is severe shortage of empirical analyses in this field, especially with regard to its acceptance. To address this gap, in this paper we use an extended technology acceptance model to empirically examine the factors affecting users' behavioural intentions towards public sector big open data. We outline the importance of our model for operations and supply chain managers, the limitations of the study, and future research directions.

ARTICLE HISTORY
Received 31 May 2016
Accepted 16 May 2017

KEYWORDS
Big open data; public sector; use; operations; supply chains

1. Introduction

In recent years there has been a redefinition of public data and the way it is being released and shared for use by different stakeholders. The value of the so-called *big open data (open data)* meets the demands of private companies and non-governmental organisations, developers and citizens; namely, the easier sharing of data across different stakeholders brings benefits that relate to its reuse for commercial purposes to public sector transparency, and decision and policy-making. As Hossain, Dwivedi, and Rana (2016) have summarised, many current factors have led to the rising need for open data: (a) the political initiative to decentralise civic services whilst enhancing public ownership of governance activities; (b) increase in technologically aware citizens equipped with digital computing skills using their discretion in accessing, analysing and distributing information at will; and (c) the proliferation of mobile and social networking platforms (Boulton et al. 2011; Huijboom and Van den Broek 2011; Zuiderwijk and Janssen 2014a). Additionally, the advancement of technology has made data exchange fairly simple in the digital space, turning users from mere recipients of data to functional producers and users of the same (Kulk and Van Loenen 2012). Finally, the spread of digital governance and associated norms, such as responsiveness, public services' accessibility, transparency, and accountability have triggered government initiatives to explore the wider prospective of distribution and use of such data (Sivarajah, Irani, and Weerakkody 2015).

From an operations and supply chain management perspective (OSCM), the use of open data has contributed in e.g. dealing with disasters and creating resilient supply chains, and generating new products and services (Rohunen et al. 2014; Shadbolt et al. 2012). Furthermore, Oberg and Graham (2016) have highlighted the use of open data for supplier and distribution networks: open data from government owned traffic systems, smart parking, and smart cities in general can be used by private companies to improve their vehicle routing and transport planning, as well as improving distribution operations for perishable products (Manville et al. 2014; Oberg and Graham 2016). In Sweden, a government-owned company is working with city planners and private companies in order to implement sensors that would manage resources such as electricity, water, traffic and waste; open data from these sensors are to be provided to organisations for the further management of their supply chains and networks (Oberg and Graham 2016).

A scrutiny of the literature indicates that several existing studies have examined the influence of big data in OSCM settings. Fosso Wamba et al. (2015a) conducted a systematic review of big data literature to synthesise the key themes and how they may impact OSCM and the business community. In another study Fosso Wamba et al. (2016) surveyed 297 Chinese IT managers and business analysts with big data and business analytic experience to examine the impact of big data on their businesses. Elsewhere, Nudurupati, Tebboune, and Hardman (2016) researched the influence of big data on performance management and measurement in the digital era while Duan and Xiong (2015) investigated key issues related to big data analytics and its applications to business problems. While these studies offer insights into big data and its value to OSCM, they do not expose the value created by big data to the public sector, particularly in the context of citizen–government interactions and relationship. As Fosso Wamba et al. (2015b, 14) points out, 'value in the context of big data implies

CONTACT Vishanth Weerakkody v.weerakkody@bradford.ac.uk

generating economically worthy insights and/or benefits, by analysing big data through extraction and transformation'. In this respect, big data can add value in a public sector context by helping to improve transparency and offering opportunities for citizens to improve their decision-making through availability and access to data around issues that matter to them.

Indeed, leading countries are investing in proactive steps to improving accessibility and efficiency of big open data (machine-readability) and associated technical standards. The dedicated data.gov.uk website is a comprehensive big open data repository displaying non-personal UK government data concerning public services (including health, social services, education, transport, crime and other geo-environmental data). The intention of opening up big data relating to public services is primarily motivated by the desire to improve the operational efficiency, accountability and transparency of government (Janssen, Charalabidis, and Zuiderwijk 2012). Although there is significant interest and endeavours around big open data in public sectors contexts, there are several existing barriers to its adoption and use. For instance, since open data is released in raw format, it is relatively difficult for users to comprehend and use the data in a meaningful manner in a day-to-day decision-making context (Sivarajah, Irani, and Weerakkody 2015). To be capable of utilising the full potential of big open data, users will have to acquire a certain degree of applied skills. Furthermore, although the availability of open data offers many opportunities for OSCM, there is no study in the literature that questions the usability of open data platforms, in particular, from a users' perspective. Therefore, both physical characteristics of big open data and the associated use related challenges provided the motivation for conducting this study; the aim therefore is to examine the factors that are capable of influencing user intentions towards the use of open data. By pursuing this aim, the paper contributes to existing knowledge by hypothesising factors that influence citizens' acceptance of big data in the context of their dealings with government and through developing a conceptual model to test these hypotheses. From a practical perspective the paper offers insights into factors that influence citizens' use intention regarding big open data in public sector and OSCM context and in this respect the areas big data that is open is easy to use (i.e. citizens should be able to use the data with minimum effort). This will help tackle one of the major challenges that the public sector currently faces in terms of the widening gap in citizens' engagement with digital government services (Carter and Weerakkody 2008; Janssen, Charalabidis, and Zuiderwijk 2012), which not only impacts the return on investment but also the sustainability of innovations and digital services in the public sector.

The remainder of the paper is structured as follows: the next section reviews the existing literature on open data, followed by a section dedicated to the development of research model and the hypotheses proposed. The analysis and findings are presented next, whereas the paper concludes with outlining of the main contributions and limitations of this study.

2. Literature: overview of big open data

Big data is a term used to describe the volume, (amount of data created each day), velocity (how quickly data can be accumulated), and the variety of data (from multiple sources including daily transactions to social networks and daily telephone conversations) (Ahmadi, Dileepan, and Wheatley 2016). The availability of big open data has grown significantly and it is seen as a way to mend the traditional separation between public organisations and users (Janssen, Charalabidis, and Zuiderwijk 2012). 'The willingness of the government to make public information that is (potentially) self-critical, or is at least perceived as unbiased, also signals to citizens that their government is functioning in a way that ultimately promotes the best interests of citizens and the society they live in' (Porumbescu 2015, 17). For governments, it is seen as a strategy that supports and motivates public organisations to release factual, non-person specific data that has been either generated or gathered via the delivery of public services to someone with a possibility of future integration, exclusive of any copyright restrictions (Bertot et al. 2014; Braunschweig et al. 2012; Hossain, Dwivedi, and Rana 2016; Kassen 2013). Increasingly, governments are imposing added pressure on all public organisations to release their raw data to the public, leading to a remarkable increase in the visibility of big open data initiatives (Janssen, Charalabidis, and Zuiderwijk 2012). The key factors encouraging public organisations to publish data are based on government's perception that the open access to publicly-funded data offers increased economic returns from public investment (Cranefield, Robertson, and Oliver 2014), access to policy-makers in addressing complex issues (Arzberger et al. 2004), generates wealth via downstream use of outputs (Janssen, Charalabidis, and Zuiderwijk 2012), and increases citizen participation in analysing large data-sets and challenging managers/authorities (Janssen, Charalabidis, and Zuiderwijk 2012; Surowiecki 2004). One of the most distinguished benefits of big open data is the increased public trust in government that allows government officials to be held accountable by the citizens (Cranefield, Robertson, and Oliver 2014; Janssen, Charalabidis, and Zuiderwijk 2012; Ubaldi 2013).

With open data, civil servants, citizens and other stakeholders (including private companies, supply chains and networks) can benefit from increased participation in government activities (Castellanos et al. 2013; Conradie and Choenni 2014), increased transparency and accountability (Cranefield, Robertson, and Oliver 2014), stimulating innovation (van Veenstra and van den Broek 2013). Big open data has a positive impact on economic growth; for instance, encouraging marketplace to develop products and services, which increase productivity, offer employment, and bring revenue back to the government in the form of taxation revenue (Borzacchiello and Craglia 2012 and Janssen, Charalabidis, and Zuiderwijk 2012). One of the societal benefits of open data also is that it allows informed and interactive citizen engagement with the government (Ubaldi 2013). Alongside the benefits are some of the challenges in using big open data, which include, upfront costs of releasing data (Cranefield, Robertson, and Oliver 2014), risk of data ownership, and privacy issues (Zuiderwijk and Janssen 2014b). Two of the most significant challenges are stimulating public interest in big open data (Ubaldi 2013; Zuiderwijk et al. 2012) and poor/low data quality which government departments may be reluctant to release (Conradie and Choenni 2014; Zhang, Zhu, and Liu 2012).

Current research on big open data is now extending beyond the organisational, systemic, and contextual effects, to also account for the push and pull effects of innovators and adopters as well as supply chains and networks (Oberg and Graham 2016). However, there are limited studies focusing on adoption intentions of big open data (Fang and Holsapple 2007; Wang and Senecal 2007; Wangpipatwong, Chutimaskul, and Papasratorn 2008). Jetzek, Avital, and Bjørn-Andersen (2012) develop a two-by-two matrix to explain value creation using social and economic values, and devise a value creation model with four propositions to be tested). Charalabidis, Loukis, and Alexopoulos (2014) test a behavioural model to examine future usage behaviour of open data users by applying technology acceptance model (TAM) variables and some variables of the IS Success Model. By employing the Innovation Diffusion Theory, Estermann (2014) survey 72 respondents to explore the costs, benefits, risks and opportunities of using open data. Meijer, Conradie, and Choenni (2014) employ the public value framework to develop an open data model, which reveals that while transparency positively influences user trust in open data, privacy has a negative impact on the same. Finally, Zuiderwijk, Janssen, and Dwivedi (2015) have researched the acceptance and use of big open data technologies. However, to the best of our knowledge, there is no published study *empirically examining the factors affecting users' intentions to use public sector open data with a focus on OSCM, giving us the impetus for this study*.

3. Research model and hypotheses development

The TAM is used in this study to examine the acceptance of public sector open data, due to its popularity in satisfactorily determining user perceptions for a system's usefulness and ease of use (Davis 1989). This model has been recognised by many studies for satisfactorily learning and managing new technology adoption (Dillon and Morris 1996; Park 2009). Since the first publication of TAM, there has been a proliferation of research models including, for instance the unified theory of acceptance and use of technology (e.g. Venkatesh et al. 2003) for effectively predicting user attitude and intentions towards technological innovations. It is interesting that all of these models use more or less similar constructs/attributes to measure technology adoption (Kapoor et al. 2014). Studies have reported TAM to be the superior performing model across different contexts – for instance, telemedicine adoption study by Chau and Hu (2001), study predicting general buyer behavioural intentions by Gentry and Calantone (2002), and RFID adoption study by Kapoor et al. (2014). Literature on innovation adoptions has witnessed extensive usage of TAM across the ICT sectors to elucidate user intentions towards the use of new solutions/technologies (Park, Nam, and Cha 2012).

It is well known that open data-sets constitute many different contexts and carry varying implications. A massive group of interdependent stakeholders have differing interests in these data-sets, which while being characteristically distinct are also contextually very different. Open data released to the public is currently being made available only in the raw format, which is not simple to understand. Adoption studies in the private sector have clear language and frameworks for understanding innovation adoptions). Some field experts have their reservations on such frameworks and consider them to be stereotypical and without sufficient empirical evidence on the intricate nature of the innovation adoption process. On-going research is extending to account for the organisational, systemic, and contextual effects, alongside the push and pull effects of the innovators and innovation adopters. Studies like Zuiderwijk, Janssen, and Dwivedi (2015) explore the acceptance and use of open data technologies, but no study tests/verifies users' intentions to use big open data. There are, however, studies that have investigated the performance of different websites. For instance, Wangpipatwong, Chutimaskul, and Papasratorn (2008) use the TAM model to evaluate the use of an e-government website. Wang and Senecal (2007) employ ease of use, speed and interactivity to measure a website's usability. Fang and Holsapple (2007) focus on the navigation structure of a website and their impact on the usability of that website by using factors defining its usability. Literature extensively supports the use of TAM constructs in measuring a new solution that is aiming to attract consumer usage based on the aspects of usefulness and ease of use (Giovanis, Binioris, and Polychronopoulos 2012; Kapoor, Dwivedi, and Williams 2013; Pei et al. 2015; Prieto, Migueláñez, and García-Peñalvo 2014; Sundarraj and Manochehri 2013). This enhances the appropriateness of the TAM being used in this study to evaluate user perceptions of public sector open data.

In addition to constructs from the TAM model, there is another pressing concern that requires attention whilst discussing the usage of open data by the citizens. There is a level of risk involved in using open data that the field experts have to deal with on a regular basis; this is of data being interpreted incorrectly by users, and the same data being used against the publisher (Dodds 2015). This concern can however be alleviated if the members of society, who have potentially used open data and put it to good use, willingly put in a good word about the pluses of using open data. This aspect of social approval is expected to motivate other members of the society in putting their worries to rest, and testing/using open data themselves before making the final adoption/rejection decision. TAM in this study will thereby be extended to include the component of *social approval* to account for the stereotype perception associated with the use of open data (more justification on the inclusion of this construct has been provided in Section 3.3).

The impact of perceived usefulness, perceived ease of use, and social approval will thus be individually examined across users' behavioural intentions. The effect of perceived ease of use will also be studied on perceived usefulness of open data (Figure 1). As suggested in the proposed model, these three characteristics are expected to significantly influence users' behavioural intentions

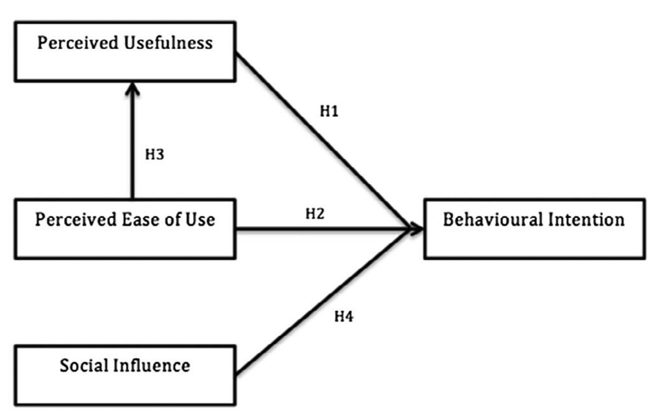

Figure 1. Modified and extended TAM model.

towards the use of open data platforms. The correlations emerging from the empirical evaluations will be logically reasoned for their role in persuading citizens towards the use of open data.

Behavioural intention, also known as use intention, is one of the most frequently used attributes in innovation-related studies (Akturan and Tezcan 2010; Kapoor, Dwivedi, and Williams 2013; Lu et al. 2008). Behavioural intention measures the likelihood of an individual being involved in certain behaviour (Ajzen and Fishbein 1980). As Chiu (2003) suggests, behavioural intention is an instinctive probability that consumers associate with the possibility of a particular behaviour. This characteristic has also been recognised by other models of innovation adoption and diffusion (TRA and TPB) as the best immediate predictor of the actual adoption of an innovation (Ozaki 2011). The behaviour of an individual, that is, their decision to accept or reject an innovative solution, is determined by their intention to perform that behaviour (Fishbein and Ajzen 1975); in this case, citizens' intention to use open data. All hypotheses proposed in this study will examine the influence of the three aforementioned variables on behavioural intentions of the study's respondents.

3.1. Perceived usefulness

Perceived usefulness is being measured to examine if the raw information available online as *big open data* is perceived by the citizens to be of relatively higher quality, in comparison to similar data that they can access using other platforms such as physical offices. In assessing the benefits of a new solution, users tend to critically evaluate the positives and negatives of using that solution or new information. Perceived Usefulness is known to determine the ultimate rate of most innovation adoptions in the long run (Pannell et al. 2006). Literature has recorded several instances where this attribute has been successfully measured for its impact on behavioural intention across numerous technologies (For example, acceptance of an online portal by Shih (2008), use of mobile Internet by Hsu, Lu, and Hsu (2007), and so on). Unless citizens see some practical worth in big open data, they are unlikely to form positive perceptions towards its usefulness. Consistent with the theoretical principles underlying the TAM model, this study proposes that perceived usefulness would have a significant and positive impact on OSCM users' intentions to use open data. Therefore:

> *H1*: Perceived usefulness will positively influence OSCM users' behavioural intentions towards the use of open data.

3.2. Perceived ease of use

Given that all of open data is released in the raw format, it is clearly not user-ready as such. Before people and businesses can use open data (severely differing in content and quality), most of it involves undergoing several layers of filtering at the legal, technical, and other stages. As witnessed, most data is negligently uploaded onto such open data websites without any clear definitions or suggestive interpretations, making it difficult for the interested stakeholders to understand and relate with the information offered over these websites (Conradie and Choenni 2014). Simple open data platforms with straightforward information are expected to enhance citizens' motivation to participate in policy-making and other governmental activities. However, the level of ease or difficulty associated with interpreting open data in the raw format will differ from person to person (Martin 2014; Raman 2012).

User knowledge of a product/service is often known to dictate individual perception of the degree of ease involved in using it. As Rogers (2003) explained, the easier a solution is to understand and implement, the faster it is accepted by the targeted users. While many studies have successfully witnessed the positive impact of this attribute on behavioural intention (for instance, Chen 2008; Sang, Lee, and Lee 2010), there is also a very significant relationship observed between ease of use and perceived usefulness. Many studies (Kapoor, Dwivedi, and Williams 2013; Schierz, Oliver Schilke, and Wirtz 2010; Venkatesh et al. 2003) support the fact that ease of using a service is often seen as a significant advantage of that service, adding to its overall usefulness. In this study, the ease of using open data websites will be examined along the aspect of optimised user experience. There is evidence in the literature that citizens and organisations refuse to rely on public sector open data based on their unfriendly user experience with open data websites; instances include failure on the part of the government to regularly update the information on such websites, and recurring problems in accessing open data (Kassen 2013). Given their raw nature, Martin (2014) concludes that open data interfaces are not user friendly, the resultant of which is limited number of users. It has been well established very early in literature that no matter how useful a new solution/service is, if it is complicated to use and understand, it will fail to attract users (Davis 1989); the resultant of which is a colossal gap between the data and its usability for the involved actor groups and stakeholders (Hunnius, Krieger, and Schuppan 2014).

Based on the aforementioned arguments, the following two hypotheses have been proposed:

> *H2*: Perceived ease of using open data will positively influence OSCM users' behavioural intentions towards its use.

> *H3*: Perceived ease of using open data will positively influence its perceived usefulness.

3.3. Social approval

Social approval often refers to the status gained in one's social group, as a certain non-financial characteristic of a reward, acting as the function of intention/adoption of a given innovation (Tornatzky and Klein 1982). The expected social or economic loss resulting from the application of a new solution prevents users from adopting that solution (Labay and Kinnear 1981). Observing a system often encourages peer discussions, which upon agreement leads to further encouragement towards the acceptance of that system within that discussion group (Rogers 2003). Ambiguity in raw data released on big open data platforms can cause user anxiety and uncertainty about its authenticity, which could be potentially alleviated if members of that user's social group vouch for its legitimacy. Thus, this study is interested in examining if the use of big open data is vulnerable to social influences. One of the prevalent issues today is not only that some government agencies and businesses are collecting personal information, but also that we are unaware of what is being collected. Social approval/influence, in the form of other people's recommendations and perceptions of an approved behavioural pattern is a strong determinant of adoption intentions (Mallat et al. 2006). Thus, measuring social approval will help identify both the level of awareness/exposure the OSCM users have about the use and benefits of big open data, and its role in positively driving user intentions.

H4: Social approval will positively influence OSCM users' behavioural intentions towards the use of open data.

4. Method

A national survey has been undertaken in the UK to understand the perceptions and intentions of OSCM users (including the public) towards the use of open data through this study. In analysing the empirical data, we will be employing different statistical techniques, and Stevens (1996) proposed that for achieving precise statistical estimates and results, a study should be aiming at a sample size of over 300. Other evidences in the literature also recommend a sample size of 300 as a respectable size (Comrey and Lee 1992). The process of gathering relevant data was outsourced to a global sampling solutions provider, SSI. This solutions company was instructed to target British citizens in their database, who have prior knowledge of open data systems and their use. The questionnaire was sent to the company, who then uploaded it onto an online survey tool. This questionnaire had one primary *dichotomous* question, where the respondents were asked if they have informed knowledge of open data systems. Only the respondents answering 'yes' to this question were allowed to continue with the rest of the questionnaire. The questionnaire also comprised of ordinal questions concerning the age group, educational qualification and income levels of the respondents.

Within a week, the survey returned 350 fully filled responses, which were then statistically analysed by the authors of this study. Questions related to the extended TAM model with four constructs (including behavioural intention) were recorded (three items/questions/statements for each). Therefore, the questionnaire for this study was designed to include 12 Likert items that had to be rated on a seven-point scale – (7) Extremely Agree (6) Quite Agree (5) Slightly Agree (4) Neutral (3) Slightly Disagree (2) Quite Disagree (1) Extremely Disagree (Appendix 2). All statements/questions were based on items that have been previously used and tested in earlier studies (Karahanna, Straub, and Chervany 1999; Moore and Benbasat 1991; Richardson 2009; Rijsdijk and Hultink 2003; Shih and Fang 2004; Teo and Pok 2003), which were suitably modified to suit the present context of open data and its impact on citizens. The questionnaire contained a brief explanation of the concept of open data alongside information on its availability and usability.

The survey questionnaire was pretested with ten respondents, who were by profession OSCM academics, researchers, and citizens having general knowledge of open data. The test respondents agreed to fill the questionnaires and report any errors in the overall design of the questionnaire, technical correctness of the contents, or any other difficulties preventing easy understanding of the questions. At first, a five-point Likert scale was employed, but upon suggestions from the academics, a seven-point scale was introduced, as they are known to prevent respondents from being increasingly neutral with their responses, and at the same time, are also considered to be more reliable. Furthermore, each item in the questionnaire was initially numbered using shorthand of the construct being measured (for instance, Ease_Use for perceived ease of use). Academics returned with suggestions of eliminating such obvious shorthand to prevent respondents from interpreting the meaning of the construct, which could potentially influence their responses. The numbering was then changed to discreet codes to prevent respondents from falling prey to any respondent bias (for instance, Ease_Use was changed to PEOU).

In assessing the appropriateness of the items used, Grover (2011) refers to a process of *content validation*. This can be based on theory for the items used in the literature, or based on the opinions of a panel of experts, who are well learned in that domain (Grover 2011). For this study, all items for the shortlisted constructs were defined by gathering the items utilised and confirmed by many studies of the past; that is, the items for this study were developed on the theoretical basis available for the shortlisted constructs in the existing literature (Appendix 1). This therefore confirmed the *content validation* of the instrument developed for this study. It ensured that the items forming the constructs were fully representative of them. The survey instrument was then pilot tested to confirm reliabilities of all shortlisted constructs. This test was run on 30 respondents, and care was taken to ensure that the population of the pilot test comprised of respondents from different age groups, gender, and educational backgrounds to test the suitability of the questionnaire. The data from the pilot test was tested for reliability and the α values for all four constructs on the reliability scale were found to be appropriate and acceptable.

5. Findings

The accumulated data were analysed using structural equation modelling (SEM) to test the proposed hypotheses by employing AMOS 21. Before undertaking SEM, the accumulated data were screened for response rates, missing cases, and potential outliers. A missing completely at random (MCAR) test was undertaken to identify missing cases and potential outliers, if any, and the nature of those missing cases to ensure their effective handling. A single test statistic checks if the cases are MCAR, whilst showing that the corresponding null distribution is asymptotically chi-squared (Little 1988). The missing value analysis test was performed using the SPSS 19 statistical tool. The univariate statistics generated for the data-set showed that there were no missing cases (Table 1). All 350 cases were therefore declared free of missing values. The responses, which are either inconsistent or particularly dissimilar than the rest of the data-set with extremely larger or smaller values, are referred to as outlying responses (Cho et al. 2013; Hair et al. 2010). The test for detecting univariate outliers was also undertaken using the SPSS 19 statistical tool, where the *Z*-scores were derived to be interpreted for the presence of probable outliers. The *Z*-scores for all attributes were lesser than the value of 4, suggesting there were no outlying responses (Hair et al. 2010). Therefore, the data-set was also declared free of outliers, and approved for the next stages of analyses.

The data-set was also tested for non-normal distribution, whereby the Kolmogorov–Smirnov statistics, the Kurtosis, and the Skewness values were all computed to interpret the distribution type. All items for the four attributes showed Kolmogorov–Smirnov values that were statistically significant (Table 2).

Overall, 350 valid responses were gathered (Table 3). The highest number of respondents (88) belonged to the 25–34 years age group, followed closely by 75 people from the 35–44 years age band. About 64 respondents were between 18 and 24 years of age, and 43 respondents fell in the 45–54 years age category. The gender distribution was found to be fairly even with 173 female respondents and slightly more number of male respondents (177 of 350). A spread of educational qualifications and annual income of the respondents has also been provided in Table 3.

Descriptive statistics for individual items of each construct have been identified in Table 4. The OSCM users rate perceived usefulness as the most important attribute, with an average mean of 4.40 (std. deviation – 1.292; variance – 1.671). Behavioural intention is considered almost equally important, with an average mean of 4.39 (std. deviation – 1.372; variance – 1.884). This is followed by perceived ease of use (Mean – 4.21; std. deviation – 1.379; variance – 1.911), and social approval receives the lowest rating with a mean of 3.95 at a std. deviation of 1.354 and variance of 1.836.

Cronbach's α is measured to establish the consistency of the attributes making up the proposed model. We tested for reliability using Cronbach's α (Santos 1999). All of the four constructs in the model have three items each. A reliability test is carried out on the survey instrument for this study (Table 5). Interestingly, all of the four attributes used in the model show high reliabilities (falling between 0.70 and 0.90). Moving forth, we examined the effects of perceived usefulness, perceived ease of use, and social approval on behavioural intention using SEM.

Confirmatory Factor Analysis was undertaken to test the measurement model (López-Gamero, Molina-Azorín, and Claver-Cortes 2009). The measurement model is a recursive over-identified model with a significant chi-square of 749.204 (p = 0.000, df = 51). The model is thus considered suitable. The model fit indices are also examined to probe into the overall model fit. The normed chi-square is reported at 2.154 (<3), making this statistic acceptable (Kline 2005). The root mean square error of approximation (RMSEA) is also well within the recommended limit of <0.07 at 0.063 (Steiger 2007; Tabachnick and Fidell 2007). The Goodness of Fit Index (GFI) and the Adjusted GFI (AGFI) values are acceptably above 0.9 (0.912) and 0.8 (0.848), respectively (Gefen, Straub, and Boudreau 2000). With the incremental fit indices, Comparative Fit Index (CFI) is very close to the desired value of 0.95 at 0.957 (Gefen, Straub, and Boudreau 2000), and the Normed Fit Index (NFI) is also acceptable at 0.962 (>0.9) (Gefen,

Table 1. Univariate statistics.

				Missing		No. of Extremes[a]	
	N	Mean	Std. deviation	Count	Per cent	Low	High
BI1	350	4.24	1.359	0	.0	37	18
BI2	350	4.42	1.353	0	.0	28	22
BI3	350	4.52	1.405	0	.0	12	0
PE1	350	4.25	1.296	0	.0	35	19
PE2	350	4.36	1.274	0	.0	31	17
PE3	350	4.61	1.308	0	.0	26	25
PEOU1	350	4.43	1.330	0	.0	28	21
PEOU2	350	4.23	1.304	0	.0	32	20
PEOU3	350	3.98	1.504	0	.0	0	0
SA1	350	3.90	1.412	0	.0	0	0
SA2	350	4.02	1.304	0	.0	49	12
SA3	350	3.93	1.346	0	.0	14	41

Notes: BI – behavioural intention; PU – perceived usefulness; PEOU – perceived ease of use; SA – social approval.
[a]Number of cases outside the range (Q1 − 1.5 × IQR, Q3 + 1.5 × IQR).

Table 3. Respondent profile.

Category	Values	Frequency	Per cent
Age	18–24	64	18.2
	25–34	88	25.1
	35–44	75	21.4
	45–54	43	12.2
	55–64	32	9.1
	65–74	33	9.4
	Above 75	15	4.2
	Total	350	100
Gender	Male	173	49.4
	Female	177	50.5
	Total	350	100
Education	Diploma	45	12.8
	Graduate	162	46.2
	Postgraduate – Taught	76	21.7
	Postgraduate – Research	35	10
	Other	32	9.1
	Total	350	100
Annual income	£10,000–£25,000	55	15.7
	£26,000–£50,000	67	19.1
	£50,000–£100,000	179	51.1
	>£100,000	49	14
	Total	350	100

Table 2. One-sample Kolmogorov–Smirnov test.

		Normal parameters		Most extreme differences				
Items	*N*	Mean	Std. deviation	Absolute	Positive	Negative	K–S	Sig
BI1	350	4.24	1.359	0.243	0.211	−0.243	4.553	0
BI2	350	4.42	1.353	0.162	0.144	−0.162	3.027	0
BI3	350	4.52	1.405	0.153	0.15	−0.153	2.859	0
PE1	350	4.25	1.296	0.245	0.209	−0.245	4.585	0
PE2	350	4.36	1.274	0.224	0.188	−0.224	4.189	0
PE3	350	4.61	1.308	0.175	0.154	−0.175	3.278	0
EE1	350	4.43	1.33	0.197	0.18	−0.197	3.692	0
EE2	350	4.23	1.304	0.212	0.212	−0.186	3.958	0
EE3	350	3.98	1.504	0.164	0.164	−0.153	3.069	0
SA1	350	3.9	1.412	0.255	0.22	−0.255	4.766	0
SA2	350	4.02	1.304	0.262	0.233	−0.262	4.894	0
SA3	350	3.93	1.346	0.24	0.237	−0.24	4.496	0

Note: K–S: Kolmogorov–Smirnov statistic.

Straub, and Boudreau 2000). Therefore, the measurement model for open data can be concluded to be of a good fit.

In discussing the discriminant and convergent validities, as already mentioned, the GFI, NFI and AGFI values are satisfactorily over the recommended values of 0.90 and 0.80, respectively. As the existing literature recommends, the chi-square value is normally expected to be statistically insignificant (Gefen, Straub, and Boudreau 2000; Hair et al. 2006; Straub, Gefen, and Boudreau 2004). However, there exists an exception for larger sample sizes. The sample size of 350 for this study is considerably large, and with the other fit statistics showing good values, the significant chi-square is considered perfectly acceptable for this study (Hooper, Coughlan, and Mullen 2008). In addition, the item loadings are above 0.5, with the majority being over 0.7. Also, all *t*-values have been reported to be acceptably significant (two-tailed at 0.001). The Average Variance Estimates (AVE) and Composite Reliability (CR) values for all latent variables have also been calculated (Table 6), which are well above 0.7, as required (Fornell and Larcker 1981; Hair et al. 2010).

The diagonal in the matrix (Table 6) shows that all AVE values are satisfactorily above 0.5. The values below this diagonal are the squared correlations for the represented pair of latent variables. The paired correlations are lower than their corresponding AVE values, which positively favour the model. With this, all conditions for confirming the discriminant and convergent validities are satisfied, confirming the overall construct validity for the open data measurement model.

Having established the construct validities, the latent variables were tested for any common method variance. In doing so, the *Harman's single factor test* was employed, whereby the *principal component analysis* was performed. The results of this test showed that no single variable accounted for majority of the variance (Table 7), that is, more than 50% (Harman 1976; Podsakoff et al. 2003). The value reported for the proposed model reported a variance of 48.43%, within the 50% mark, indicating there was no common method bias in the data-set for this study.

The hypothesised relationships are next introduced between the latent variables in the measurement model. The fit statistics for the structural model (Figure 2) have been recorded in Table 8.

Four hypotheses were established for examining the acceptance of big open data in the public sector. All of the four hypotheses are supported by the gathered data (H1, H2, H3, and H4). The chi-square value for this model is reported significant at 845.404 ($p = 0.000$) with 54 degrees of freedom. The other fit indices were also examined, and it was found that the CFI (0.953 > 0.95), GFI (0.940 > 0.9), AGFI (0.803 > 0.8), and RMSEA (0.058 < 0.070) values are all well aligned with their recommended values. The CMIN/df value at 2.459 is also well below 3. The NFI value is above 0.9 at 0.987. Again, fit statistics meet their recommended values, and a

Table 4. Descriptive statistics.

	N	Mean	Std. deviation	Variance
Items	Statistic	Statistic	Statistic	Statistic
BI1	350	4.24	1.359	1.846
BI2	350	4.42	1.353	1.831
BI3	350	4.52	1.405	1.975
Average BI	350	4.39	1.372	1.884
PU1	350	4.25	1.296	1.680
PU2	350	4.36	1.274	1.623
PU3	350	4.61	1.308	1.712
Average PU	350	4.40	1.292	1.671
PEOU1	350	4.43	1.330	1.770
PEOU2	350	4.23	1.304	1.700
PEOU3	350	3.98	1.504	2.263
Average PEOU	350	4.21	1.379	1.911
SA1	350	3.90	1.412	1.995
SA2	350	4.02	1.304	1.701
SA3	350	3.93	1.346	1.812
Average SA	350	3.95	1.354	1.836

Notes: BI – behavioural intention; PU – perceived usefulness; PEOU – perceived ease of use; SA – social approval.

Table 5. Reliability test.

Constructs	Sample	Items	Cronbach's α	Reliability
Perceived usefulness	350	3	.871	High
Perceived ease of use	350	3	.841	High
Social approval	350	3	.880	High
Behavioural intention	350	3	.826	High

Table 6. AVE and CR values.

Latent variables	CR values	BI	PEOU	PU	SA
Behavioral Intention (BI)	0.926	**0.723**			
Perceived Ease of Use (PEOU)	0.762	0.428	**0.589**		
Perceived usefulness (PU)	0.739	0.261	0.521	**0.534**	
Social Approval (SA)	0.714	0.221	0.429	0.332	**0.521**

Notes: CR – composite reliability; Values in bold – AVE values; Others – squared correlations.

Table 7. Principal component analysis.

	Initial eigenvalues			Extraction sums of squared loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	5.812	48.437	48.437	5.812	48.437	48.437
2	2.085	17.372	65.809			
3	.855	7.125	72.933			
4	.642	5.348	78.282			
5	.565	4.707	82.988			
6	.424	3.536	86.525			
7	.352	2.937	89.462			
8	.292	2.429	91.892			
9	.281	2.344	94.236			
10	.245	2.046	96.281			
11	.228	1.899	98.181			
12	.218	1.819	100.000			

Note: Extraction method: principal component analysis.

big sample size ($n = 350$) used for this SEM, makes the significant chi-square of 845.404 acceptable for this model. Alike the measurement model, the structural model for open data also displays a good model fit.

Table 8 shows that this model has two endogenous and three exogenous latent variables. Of the two endogenous variables, *behavioral intention*, explains 58% variance (SMC = 0.58) and *perceived usefulness* explains 49% variance (SMC = 0.49). Straub, Gefen, and Boudreau (2004) suggest 0.40 and above to be the acceptable adjusted R^2 value, therefore, the SMC values reported herein are contributing towards an acceptable level of predictability for the structural model used in this study. It is clear from the SEM results that perceived usefulness ($\beta = 0.68$, $p = .002$) is the strongest predictor of citizens' intentions to use open data, and perceived ease of use is a good predictor of the usefulness of open data ($\beta = 0.36$, $p = .000$).

The functional value of open data is measured using perceived usefulness (Figure 2). In rating the perceived usefulness of open data, about 45% respondents were neutral about the opinion that open data is useful in making day-to-day decisions (PU1). With most people again being neutral, about 25% people slightly agreed that open data helped them make better decisions (PU2, Table 9). While 30% respondents were neutral about the idea, 55% agreed that open data helped their understanding of governmental actions that directly affect them as citizens (PU3).

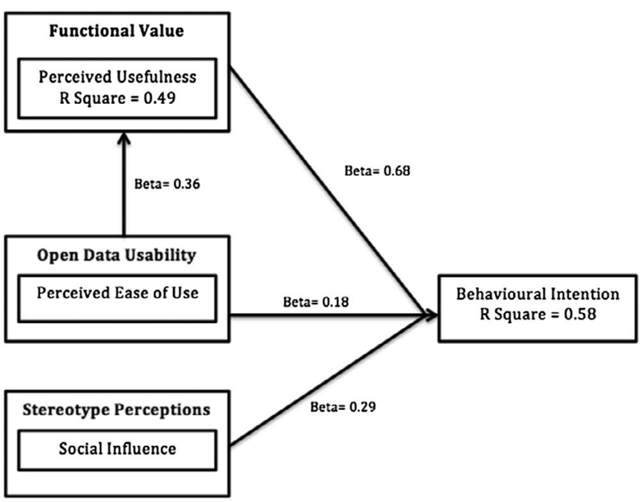

Figure 2. Validated research model.

About 38% respondents were neutral about open data being easy to use (PEOU1). Then there were 19% respondents who slightly agreed on open data websites being challenging and frustrating to use (PEOU2). While 29% believed that their understanding of open data was very clear, 32% were neutral with their opinion of it, and 30% denied the same (PEOU3, Table 10).

With most people being neutral about people important to them recommending the use of open data (47%), 25% had social approval on using open data (SA1). While 28% respondents had their friends, family, and colleagues support their use of open data, an almost equal proportion of respondents (23%) denied any such support from their social circle (SA2). With almost half of the respondent population being neutral about the statement – people who influence my behaviour think I should use open data, 24% agreed to the same (SA3, Table 11).

In rating the responses for items related to behavioural intentions, about 36% respondents planned to use open data, as they believed that the central idea of such data is to create transparency within a democracy (BI1). A good percentage of respondents (48%) said that despite them being aware of the benefits of open data, their personal willingness to use open data is not high (BI2). Again, with 30% respondents being neutral of the use of open data, about 49% said that the likelihood of them using open data was not very high (BI3, Table 12).

6. Discussion and implications

6.1. Theoretical contribution

Numerous studies have employed TAM in investigating users' intentions towards the acceptance of a given solution or service (Park, Nam, and Cha 2012). Behavioural intention is considered the intuitive likelihood that a user directly relates with the probability of performing/displaying certain behaviour (Chiu 2003). Most models unanimously recognise behavioural intention as the best predictor of user behaviour (Lee and Rao 2009; Ozaki 2011). A total of four hypotheses were examined to determine

Table 8. Statistical estimates for the structural model.

Independent and dependent variable relationships		Estimates		
Independent variables	Dependent variables	β	C.R.	p
Perceived usefulness	Behavioural intention	0.68	3.705	0.002
Perceived ease of use	Behavioural intention	0.18	2.293	0.000
Social approval	Behavioural intention	0.29	2.733	0.008
Perceived ease of use	Perceived usefulness	0.36	3.423	0.000
R^2 for perceived usefulness		0.49		
R^2 for behavioural intention		0.58		
Chi-square (χ^2)		845.404		
Probability level		0.000		
Degrees of freedom		54		
CMIN/df (χ^2/df)		2.459		
Comparative Fit Index, CFI		0.953		
Goodness of Fit, GFI		0.940		
Adjusted Goodness of Fit, AGFI		0.803		
Normed Fit Index, NFI		0.987		
Root mean square error of approximation, RMSEA		0.058		
Sample size		350		

the effects of three predictor variables (perceived usefulness, perceived ease of use, and social approval) of this study on users' behavioural intentions (H1, H2, H4), and their perceptions of usefulness of open data (H3). Our findings suggest that users still have their doubts about the level of transparency in open data and the degree of corruption in government functions (O'Hara 2011) with respondents showing limited willingness to use open data (see Table 8). With almost half of the respondent population not being certain of the advantages of open data and its importance in their everyday life (Section 5, Table 5), it is quite evident that users lack knowledge and exposure on the subject. Before they can harness the benefits of open data, they have to be educated on the usefulness of these data being released by the government, which is mostly in their interest and give them the opportunity of being involved in policy-making and governmental decisiony-making.

Innovation adoption studies consider perceived usefulness a very strong determinant of favourable use intentions. The governing idea behind open data and platforms offering such data is to make it simpler for citizens to gain access to some of the government data, which is expected to facilitate civic engagement in government decisions (Martín, de Rosario, and Pérez 2015). By releasing such information, government enables citizens to see the usefulness of this data in increasing transparency in government functions, and also invites their participation in future policy-making decisions that would directly affect them on a daily basis (Conradie and Choenni 2014; Janssen, Charalabidis, and Zuiderwijk 2012). As proposed in hypothesis H1 of this study, this study confirms a positive and significant impact of *perceived usefulness* on *behavioural intentions* of the open data users. With H1 being supported by the data gathered in this study, it can be stated that UK users have positive ideas regarding the usefulness of public sector open data. This behaviour of perceived usefulness is also backed by earlier studies across different technologies (Hess, McNab, and Basoglu 2014; Liaw and Huang 2013; Purnawirawan, De Pelsmacker, and Dens 2012).

As already emphasised in the paper, open data released in raw format comes with the drawback of limited understanding and interpretation. From the government perspective, one of their motives behind releasing big open data is to encourage technically skilled users to use this data for designing and developing creative applications, supply networks, improving operations and supply chains, and providing tools to engage and serve the wider community – citizens, businesses, public sector organisations, and independent developers (Kassen 2013; Martín, de Rosario, and Pérez 2015; Oberg and Graham 2016). As hypothesised in H2 and H3, this study confirms the positive and significant influences of both *perceived ease of use* on *behavioural intentions* and *perceived ease of using open data* on its *perceived usefulness*. The significance of these two relationships has been massively supported by previous studies under varying contexts including, for instance, IT acceptance (Kim et al. 2009). This result bodes well for public sector institutions who wish to make their data open to the public, but also offers insights into the importance of ensuring that any big data that is open is easy to use (i.e. citizens should be able to use the data with minimum effort). This will help tackle one of the major challenges that the public sector currently faces in terms of the widening gap in citizens' engagement with digital government services (Carter and Weerakkody 2008; Janssen, Charalabidis, and Zuiderwijk 2012), which not only impacts the return on investment but also the sustainability of innovations and digital services in the public sector.

The quality of information available on the Internet is open to manipulation, and hence questionable in terms of its reliability

Table 9. Frequencies for perceived usefulness.

Perceived usefulness	Extremely disagree	Disagree	Slightly disagree	Neutral	Slightly agree	Agree	Extremely agree
PU1	13	22	27	159	78	32	19
PU2	10	21	27	144	89	42	17
PU3	8	18	25	106	113	55	25

Table 10. Frequencies for perceived ease of use.

Perceived ease of use	Extremely disagree	Disagree	Slightly disagree	Neutral	Slightly agree	Agree	Extremely agree
PEOU1	11	17	34	132	83	52	21
PEOU2	6	26	54	139	67	38	20
PEOU3	18	43	62	111	55	42	19

Table 11. Frequencies for social approval.

Social approval	Extremely disagree	Disagree	Slightly disagree	Neutral	Slightly agree	Agree	Extremely agree
SA1	20	49	27	166	40	35	13
SA2	15	34	32	173	51	33	12
SA3	14	42	42	167	44	23	18

Table 12. Frequencies for behavioural intention.

Behavioural intention	Extremely disagree	Disagree	Slightly disagree	Neutral	Slightly agree	Agree	Extremely agree
BI1	18	19	28	159	65	43	18
BI2	10	18	48	107	96	49	22
BI3	12	13	46	106	83	63	27

(Hand 2012). With big open data available for anyone to build applications, there are possibilities for human errors leading thereby to wrong decisions on the basis of incorrect information available in the form of open data. However, early adoption of a solution in a member's social circle has the potential to trigger a bandwagon effect (Abrahamson and Rosenkopf 1997). If members of a social group who have tried and tested open data vouch for its usefulness, it will be perceived as a form of social approval by the other members of the system, with them in turn forming positive intentions of employing open data in their future decisions. Information exchange and social interaction play a massive role in promoting innovation adoption (Bandura 1986). In addressing the stereotype perception for this study, hypothesis H4 was supported by the gathered data, with a positive and significant effect of *social approval* being recorded on OSCM users' behavioural intentions to use open data. Social approval is regarded as one of the components of perceived usefulness (Moore and Benbasat 1991). This component measures the degree to which the members of a social system approve the usage of a certain product/service (Lopez-Nicolas, Molina-Castillo, and Bouwman 2008). Many studies in the literature have confirmed positive results of social approval on user intentions (Claudy, Michelsen, and O'Driscoll 2011; Lee et al. 2011; Shin 2010).

6.2. Managerial implications

Local and central governing departments have made open data one of their priorities; conceptualising its usefulness from a user's standpoint offers new insights to policy-makers and researchers for efficiently tackling the spread and use of public sector big open data in the UK. It is well known that currently, open data is being regarded highly within the administrative and management structures in the UK, and yet the literature has no evidence/record of a conceptual model or instrument that can be used to assess the willingness and intentions of users towards open data. . The value of big open data in a public sector context will only be realised if it contributes to improving transparency, trust and decision-making capabilities of citizens who will use it (Janssen, Charalabidis, and Zuiderwijk 2012; Sivarajah, Irani, and Weerakkody 2015). Therefore, understanding how citizens perceive big open data and their willingness to accept it is vital for policy-makers and practitioners engaged in developing and releasing big data repositories in a public sector context. In this respect, the research model proposed and validated in this study can thus be used as a normative source for understanding user perceptions of public sector open data.

The findings presented in this paper can be used by the digital government policy-makers and practitioners in the UK as well as from operations and supply chain managers to gain first-hand knowledge of understanding of big open data. Insights from the study can be used to motivate more government institutions to develop useful and easy to use big open data repositories as part of their digital government strategy; this can facilitate the improved engagement of citizens in public sector decision-making processes and contribute towards improving the efficiency of public services. Also, the conclusions from this study can be used as a base reference to build up on an extensive international model/study, where their significance and validity can be evaluated for scalability. The findings from this study clearly suggest that OSCM users are interested in incorporating open data, if there is evidence of it being useful and more insightful in comparison to other data forms, and also, importantly, if it is easy to understand and use.

The government initiatives promoting open data to bring about transparency in government functions appear to be a success, particularly with current users approving the usefulness of this data in encouraging the members of their social group to use open data. As also revealed in this study, the percentage of users forming positive use intentions is not high. This calls for continued efforts from the government and operations and supply chain managers in ensuring that meaningful and easily interpretable data with clear benefits reaches the users to achieve high/intended number of open data users.

7. Conclusions, limitations and future research directions

Studying available literature and reviewing the secondary information on open data suggests that public sector open data is being released in the best interest of citizens and business communities. The manner in which stakeholders access and use open data is governed by the manner in which such data is published (Braunschweig et al. 2012). However, a good look at the open data resources and platforms reveals that all of the released information is in the form of raw data files. This information is very poorly structured, often with overlapping contexts, being of no potential use to a layman without sound technical knowledge. Such confusing information results in loss of citizen interest in such open data platforms, with the potential impact of open data remaining unexplored.

Clearly, one of the biggest challenges for big open data publishers is making it come to life, and hence the conscious efforts in encouraging skilled users to reorganise existing data to offer useful visualisations for the end users (Data gov 2016). Governing bodies releasing such data expect technically equipped users (software developers and coding experts) to exploit the released data in its raw format and develop meaningful applications and tools for the benefit of the society (Data gov 2016). The output of this exercise is expected to be simplified and orderly grouping of raw data for it to be usable by the public, for instance – (a) to undertake comparative analysis of trends across different policy areas over time; and/or (b) gain a general understanding of different government functions.

Despite continued governmental initiatives through hackathons, workshops and conferences, there limited, if any, information on the factors governing user perceptions and intentions to use open data technologies. In this study, two attributes from the TAM model alongside social approval are aimed at exploring different aspects spread across – the functional value of big open data (perceived usefulness), its usability (perceived ease of use), and a stereotype perception associated with its use (social approval). SEM undertaken for this study with its empirical findings suggests that *perceived usefulness of open data* is the strongest predictor of OSCM users' *behavioural intention* towards its potential use. Also, *perceived ease of use* and *social approval* positively and significantly predict behavioural intentions of the users towards the use of open data. To further add, an additional relationship between perceived usefulness and perceived ease of use showed a positive influence of the latter over the former. Implicitly, this suggests that users find easy to use open data as one of its advantages, thereby resulting in them forming positive intentions about the usefulness of public sector open data in their everyday lives.

In acknowledging the limitations of this study the following points have been identified. Public sector open data is still in its nascent stage, and given its raw data format, its relevance and benefits are limited. This only allowed the study to examine the constructs for their influence on intention to use open data, and not on the actual adoption of open data. This study intends to extend it findings at a future point in time for the adoption aspect of open data; with strategies in place, open data is soon expected to reach more number of users, particularly, the data from local governments and local services which will be of direct relevance to the public. Although the survey company was instructed to gather data from users having prior knowledge of open data, the survey results showed significant percentage of neutral responses (see Tables 5-8). Future research will target a more focused set of respondents, with them having considerable knowledge and genuine experience of open data usage; this will ensure the survey outcome is truly user oriented. With only three constructs (TAM) examined within this study, the future aim is to study the role of other adoption factors (such as compatibility, observability, visibility, result demonstrability, image and so on) and their effects on user intentions to use open data. Finally, the authors of this paper also intend to determine how big open data can contribute to improved life quality whilst fostering innovative, sustainable digital solutions and services in the public sector.

Disclosure statement

No potential conflict of interest was reported by the authors.

Notes on contributors

Vishanth Weerakkody is a professor of Management Information Systems and Governance in the Faculty of Management and Law at University of Bradford. Prior to his academic career, he worked in a number of Multinational organisations in the area of software engineering, business systems design and process analysis. He is currently involved in several R&D projects which are funded by the European Commission and International bodies such as the Qatar Foundation. He has published over 150 peer-reviewed research articles, guest-edited special issues of leading journals and edited several books on these themes. Vishanth has many years of R&D experience in the field of ICT innovation, process transformation and digital governance and is currently the editor-in-chief of the International Journal of Electronic Government Research.

Kawaljeet Kapoor is a research fellow in the School of Business at Brunel University London. Her present research is focused on IT adoption and Social Innovation. She has a PhD in Business Management, and an MBA, both from Swansea University, Wales, and a bachelor's degree in Mechanical Engineering. She has first/co-authored many publications for international refereed journals including ISF, ISM, TMR, and others. She also has three years of industry experience from working as a software engineer at Accenture Services, India.

Maria Elisavet Balta is a senior lecturer in Human Resource Management at Kent Business School. Her research lies in the area of management with specific interest in the following areas: strategic and human resource management, gender and entrepreneurship and social entrepreneurship. Her recent outcome appears in Organization (3*) and in Work, Employment and Society (4*) and also a book chapter on employee retention strategies has been accepted by Cambridge University Press for the International Human Resource Management textbook. Her research has received a significant amount of funding from the European Commission for the ERASMUS+ 2015 project on Social and Sustainable Fashion Entrepreneurs (€207.52,600) and also the BRIEF award on the project that explores the key drivers for entrepreneurial growth: A gendered perspective (£12,574).

Zahir Irani is the dean of Management and Law in the Triple Accredited Faculty at the University of Bradford, (UK). Prior to this role, he was the Founding Dean of College (Business, Arts and Social Sciences) at Brunel University (UK) and has previously worked for the UK Government as a senior policy advisor in the Cabinet Office. He has published extensively in 3* and 4* academic journal in areas such as Information Systems, eGovernment, Operations Management and has attracted research funds from the EU, EPSRC, ESRC, QNRF and various industry sources. He tweets at: ZahirIrani1.

Yogesh K. Dwivedi is a professor of Digital and Social Media, director of the Emerging Markets Research Centre (EMaRC), and director of Research in the School of Management at Swansea University, Wales, UK. His research interests are in the area of Information Systems (IS) including the adoption and diffusion of emerging ICTs and digital and social media marketing. He has published more than 150 articles in a range of leading academic journals and conferences. He has co-edited/co-authored more than 15 books on technology adoption, e-government and IS theory. He has acted as co-editor of fifteen special issues; organised tracks, mini-tracks and panels in leading conferences; and served as programme co-chair of IFIP WG 8.6 Conference and Conference Chair of IFIP WG 6.11 I3E2016 Conference. He is an associate editor of European Journal of Marketing and Government Information Quarterly and a senior editor of Journal of Electronic Commerce Research. More information: http://www.swansea.ac.uk/staff/som/academic-staff/y.k.dwivedi/.

References

Abrahamson, E., and L. Rosenkopf. 1997. "Social Network Effects on the Extent of Innovation Diffusion: A Computer Simulation." *Organization Science* 8 (3): 289–309.

Ahmadi, M., P. Dileepan, and K. K. Wheatley. 2016. "A SWOT Analysis of Big Data." *Journal of Education for Business* 91: 289–294. doi:10.1080/08832323.2016.1181045.

Ajzen, I., and M. Fishbein. 1980. *Understanding Attitudes and Predicting Social Behavior*. Engle-wood-Cliffs, NJ: Prentice-Hall.

Akturan, U. L. U. N., and Tezcan, N. U. R. A. Y. 2010. "The Effects of Innovation Characteristics on Mobile Banking Adoption." Paper presented at the 10th Global Conference on Business and Economics, Rome.

Arzberger, P., P. Schroeder, A. Beaulieu, G. Bowker, K. Casey, L. Laaksonen, and P. Wouters. 2004. "An International Framework to Promote Access to Data." *Science and Government* 303 (5665): 1777–1778.

Bandura, A. 1986. *Social Foundations of Thoughts and Action: A Social Cognitive Theory*. Englewood Cliffs, NJ: Prentice-Hall.

Bertot, J. C., U. Gorham, P. T. Jaeger, L. C. Sarin, and H. Choi. 2014. "Big Data, Open Government and E-Government: Issues, Policies and Recommendations." *Information Polity* 19 (1): 5–16.

Borzacchiello, M. T., and M. Craglia. 2012. "The Impact on Innovation of Open Access to Spatial Environmental Information: A Research Strategy." *International Journal of Technology Management*. 60 (1/2): 114–129.

Boulton, G., M. Rawlins, P. Vallance, and M. Walport. 2011. "Science as a Public Enterprise: The Case for Open Data." *The Lancet* 377 (9778): 1633–1635.

Braunschweig, K., J. Eberius, M. Thiele, and W. Lehner. 2012. "The State of Open Data Limits of Current Open Data Platforms." *CiteSeer*. Accessed May 27, 2016. http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.309.8903

Carter, L., and V. Weerakkody. 2008. "E-Government Adoption: A Cultural Comparison." *Information Systems Frontiers, Springer* 10 (4): 473–482.

Castellanos, M., F. Daniel, I. Garrigós, and J. N. Mazón. 2013. "Business Intelligence and the Web." *Information Systems Frontiers* 15 (3): 307–309.

Charalabidis, Y., E. Loukis, and C. Alexopoulos. 2014. "Evaluating Second Generation Open Government Data Infrastructures Using Value Models." Paper presented at the 2014 47th Hawaii International Conference on System Sciences.

Chau, P. Y., and P. J. H. Hu. 2001. "Information Technology Acceptance by Individual Professionals: A Model Comparison Approach." *Decision Sciences* 32 (4): 699–719.

Chen, L.-D. 2008. "A Model of Consumer Acceptance of Mobile Payment." *International Journal of Mobile Communications* 6 (1): 32–52.

Chiu, R. K. 2003. "Ethical Judgment and Whistleblowing Intention: Examining the Moderating Role of Locus of Control." *Journal of Business Ethics* 43 (1/2): 65–74.

Cho, H. Y., J. H. Oh, K. O. Kim, and J. S. Shim. 2013. "Outlier Detection and Missing Data Filling Methods for Coastal Water Temperature Data." In *Proceedings of the 12th International Coastal Symposium (Plymouth, England), Journal of Coastal Research*, edited by D. C. Conley, G. Masselink, P. E. Russell and T. J. O'Hare, *Journal of Coastal Research*, Special Issue No. 65, 1898–1903.

Claudy, M. C., C. Michelsen, and A. O'Driscoll. 2011. "The Diffusion of Microgeneration Technologies – Assessing the Influence of Perceived Product Characteristics on Home Owners' Willingness to Pay." *Energy Policy* 39 (3): 1459–1469.

Comrey, A. L., and H. B. Lee. 1992. *A First Course in Factor Analysis*. 2nd ed. Hillsdale, NJ: Erlbaum.

Conradie, P., and S. Choenni. 2014. "On the Barriers for Local Government Releasing Open Data." *Government Information Quarterly* 31 (1): S10–S17.

Cranefield, J., O. Robertson, and G. Oliver. 2014. "Value in the Mash: Exploring the Benefits, Barriers and Enablers of Open Data Apps." Paper presented at the European Conference on Information Systems (ECIS) 2014, Tel Aviv, Israel, June 9–11, ISBN 978-0-9915567-0-0.

Data gov. 2016. Accessed April 20, 2016. www.data.gov.uk

Davis, F. D. 1989. "Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology." *MIS Quarterly* 13 (3): 319–340.

Dillon, A., and M. G. Morris. 1996. "User Acceptance of Information Technology: Theories and Models." *Annual Review of Information Science and Technology* 31: 3–32.

Dodds, L. 2015. "Managing Risks When Publishing Open Data." Accessed January 16, 2016. http://blog.ldodds.com/2015/11/15/managing-risks-when-publishing-open-data/

Duan, L., and Y. Xiong. 2015. "Big Data Analytics and Business Analytics." *Journal of Management Analytics* 2 (1): 1–21.

Dwivedi, Y. K., and Z. Irani. 2009. "Understanding the Adopters and Non-Adopters of Broadband." *Communications of the ACM* 52 (1): 1–4.

Estermann, B. 2014. "Diffusion of Open Data and Crowdsourcing among Heritage Institutions: Results of a Pilot Survey in Switzerland." *Journal of Theoretical and Applied Electronic Commerce Research* 9 (3): 15–31.

Fang, X., and C. W. Holsapple. 2007. "An Empirical Study of Web Site Navigation Structures' Impacts on Web Site Usability." *Decision Support Systems* 43 (2): 476–491.

Fishbein, M., and I. Ajzen. 1975. *Belief, Attitude, Intention, and Behavior: An Introduction to Theory and Research*. Reading, MA: Addison-Wesley.

Fornell, C., and D. Larcker. 1981. "Structural Equation Models with Unobservable Variables and Measurement Error." *Journal of Marketing Research* 18 (1): 39–50.

Fosso Wamba, S., S. Akter, T. Coltman, and E. W. T. Ngai. 2015a. "Guest Editorial: Information Technology Enabled Supply Chain Management." *Production Planning and Control* 26 (12): 933–944.

Fosso Wamba, S., S. Akter, A. Edwards, G. Chopin, and D. Gnanzou. 2015b. "How 'Big Data' Can Make Big Impact: Findings from a Systematic Review and a Longitudinal Case Study." *International Journal of Production Economics* 165 (1): 234–246.

Fosso Wamba, S., A. Gunasekaran, S. Akter, S. J. Ren, R. Dubey, and S. J. Childe. 2016. "Big Data Analytics and Firm Performance: Effects of Dynamic Capabilities." *Journal of Business Research* 70 (1): 356–365.

Gefen, D., D. W. Straub, and M. Boudreau. 2000. "Structural Equation Modeling and Regression: Guidelines for Research Practice." *Communications of AIS* 4 (7): 1–79.

Gentry, L., and R. Calantone. 2002. "A Comparison of Three Models to Explain Shop Bot Use on the Web." *Psychology & Marketing* 19 (11): 945–956.

Giovanis, A. N., S. Binioris, and G. Polychronopoulos. 2012. "An Extension of TAM Model with IDT and Security/Privacy Risk in the Adoption of Internet Banking Services in Greece." *EuroMed Journal of Business* 7 (1): 24–53.

Grover, V. 2011. "A Tutorial on Survey Research: From Constructs to Theory." Accessed February 9, 2014. http://people.clemson.edu/~vgrover/survey/MIS-SUVY.html

Hair, J. F., Jr., W. C. Black, B. J. Babin, and R. E. Anderson. 2010. *Multivariate Data Analysis. A Global Perspective*. 7th ed. Upper Saddle River, NJ: Pearson Education.

Hair, J., W. Blake, B. Babin, and R. Tatham. 2006. *Multivariate Data Analysis*. 6th ed. Upper Saddle River, NJ: Prentice Hall.

Hand, D. 2012. "Open Data is a Force for Good, but Not without Risks." *The Guardian*, July 10. Accessed November 6, 2015. http://www.theguardian.com/society/2012/jul/10/open-data-force-for-good-risks

Harman, H. H. 1976. *Modern factor analysis*. University of Chicago Press.

Hess, T. J., A. L. McNab, and K. A. Basoglu. 2014. "Reliability Generalization of Perceived Ease of Use, Perceived Usefulness, and Behavioral Intentions." *MIS Quarterly* 38 (1): 1–28.

Hooper, D., J. Coughlan, and M. Mullen. 2008. "Structural Equation Modelling: Guidelines for Determining Model Fit." *Electronic Journal of Business Research Methods* 6 (1): 53–60.

Hossain, M. A., Y. K. Dwivedi, and N. P. Rana. 2016. "State-of-the-Art in Open Data Research: Insights from Existing Literature and a Research Agenda." *Journal of Organizational Computing and Electronic Commerce* 26 (1–2): 14–40.

Hsu, C. L., H. P. Lu, and H. H. Hsu. 2007. "Adoption of the Mobile Internet: An Empirical Study of Multimedia Message Service (MMS)." *Omega* 35 (6): 715–726.

Huijboom, N., and T. Van den Broek. 2011. "Open Data: An International Comparison of Strategies." *European Journal of ePractice* 12 (1): 1–13.

Hunnius, S., B. Krieger, and T. Schuppan. 2014. "Providing, Guarding, Shielding: Open Government Data in Spain and Germany." Paper presented at the European Group for Public Administration Annual Conference, Speyer, Germany.

Janssen, M., Y. Charalabidis, and A. Zuiderwijk. 2012. "Benefits, Adoption Barriers and Myths of Open Data and Open Government." *Information Systems Management* 29 (4): 258–268.

Jetzek, T., M. Avital, and N. Bjørn-Andersen. 2012. "The Value of Open Government Data: A Strategic Analysis Framework." Paper presented at the 2012 Pre-ICIS Workshop.

Kapoor, K., Y. Dwivedi, N. C. Piercy, B. Lal, and V. Weerakkody. 2014. "RFID Integrated Systems in Libraries: Extending TAM Model for Empirically Examining the Use." *Journal of Enterprise Information Management* 27 (6): 731–758.

Kapoor, K., Y. K. Dwivedi, and M. D. Williams. 2013. "Role of Innovation Attributes in Explaining the Adoption Intention for the Interbank Mobile Payment Service in an Indian Context." Paper presented at Grand Successes and Failures in IT Public and Private Sectors, 203–220. Springer Berlin Heidelberg.

Karahanna, E., D. W. Straub, and N. L. Chervany. 1999. "Information Technology Adoption across Time: A Cross-sectional Comparison of Pre-adoption and Post-adoption Beliefs." *MIS Quarterly* 23 (2): 183–213.

Kassen, M. 2013. "A Promising Phenomenon of Open Data: A Case Study of the Chicago Open Data Project." *Government Information Quarterly* 30 (4): 508–513.

Kim, C., E. Oh, N. Shin, and M. Chae. 2009. "An Empirical Investigation of Factors Affecting Ubiquitous Computing Use and U-business Value." *International Journal of Information Management* 29 (6): 436–448.

Kline, R. B. 2005. *Principles and Practice of Structural Equation Modeling*. 2nd ed. New York, NY: The Guilford Press.

Kulk, S., and B. Van Loenen. 2012. "Brave New Open Data World?" *International Journal of Spatial Data Infrastructures Research* 7 (1): 196–206.

Labay, D. G., and T. C. Kinnear. 1981. "Exploring the Consumer Decision Process in the Adoption of Solar Energy Systems." *Journal of Consumer Research* 8 (3): 271–278.

Lee, J., and H. R. Rao. 2009. "Task Complexity and Different Decision Criteria for Online Service Acceptance: A Comparison of Two E-Government Compliance Service Domains." *Decision Support Systems* 47 (4): 424–435.

Lee, D., I. Son, M. Yoo, and J. H. Lee. 2011. "Understanding the Adoption of Convergent Services: The Case of IPTV." Paper presented at the System Sciences (HICSS), 44th Hawaii International Conference. IEEE.

Liaw, S. S., and H. M. Huang. 2013. "Perceived Satisfaction, Perceived Usefulness and Interactive Learning Environments as Predictors to Self-regulation in E-Learning Environments." *Computers & Education* 60 (1): 14–24.

Little, R. J. 1988. "A Test of Missing Completely at Random for Multivariate Data with Missing Values." *Journal of the American Statistical Association* 83 (404): 1198–1202.

López-Gamero, M. D., J. F. Molina-Azorín, and E. Claver-Cortes. 2009. "The Whole Relationship between Environmental Variables and Firm Performance: Competitive Advantage and Firm Resources as Mediator Variables." *Journal of Environmental Management* 90 (10): 3110–3121.

Lopez-Nicolas, C., F. J. Molina-Castillo, and H. Bouwman. 2008. "An Assessment of Advanced Mobile Services Acceptance: Contributions from TAM and Diffusion Theory Models." *Information and Management* 45 (6): 359–364.

Lu, J., C. Liu, C.-S. Yu, and K. Wang. 2008. "Determinants of Accepting Wireless Mobile Data Services in China." *Information and Management* 45 (1): 52–64.

Mallat, N., M. Rossi, V. K. Tuunainen, and A. Oorni. 2006. "The Impact of Use Situation and Mobility on the Acceptance of Mobile Ticketing Services." Paper presented at the 39th Hawaii International Conference on System Sciences.

Manville, C. G., J. Cochrane, J. Cave, J. K. Millard, R. K. Pederson, A. Thaarup, M. Liebe, R. Massink Wissner, and B. Kotterink. 2014. "Mapping Smart Cities in the EU." European Parliament. Accessed May 21, 2016. http://www.europarl.europa.eu/studies

Martin, C. 2014. "Barriers to the Open Government Data Agenda: Taking a Multi-level Perspective." *Polymer International* 6 (3): 217–240.

Martín, A. S., A. H. de Rosario, and C. C. Pérez. 2015. "Open Government Data: A European Perspective." In *Information and Communication Technologies in Public Administration: Innovations from Developed Countries*, edited by G. R. Christopher and L. Anthopoulos, 3–28. Boca Raton, FL: CRC Press.

Meijer, R., P. Conradie, and S. Choenni. 2014. "Reconciling Contradictions of Open Data regarding Transparency, Privacy, Security and Trust." *Journal of Theoretical and Applied Electronic Commerce Research* 9 (3): 32–44.

Moore, G. C., and I. Benbasat. 1991. "Development of an Instrument to Measure the Perceptions of Adopting an Information Technology Innovation." *Information Systems Research* 2 (3): 192–222.

Nudurupati, S. S., S. Tebboune, and J. Hardman. 2016. "Contemporary Performance Measurement and Management (PMM) in Digital Economies." *Production Planning & Control* 27 (3): 226–235.

O'Hara, K. 2011. *Transparent Government, Not Transparent Citizens: A Report on Privacy and Transparency for the Cabinet Office*, 84 pp. London: GB, Cabinet Office. Accessed May 27, 2016. http://eprints.soton.ac.uk/272769/

Oberg, C., and G. Graham. 2016. "How Smart Cities Will Change Supply Chain Management: A Technical Viewpoint." *Production Planning & Control* 27 (6): 529–538.

Ozaki, R. 2011. "Adopting Sustainable Innovation: What Makes Consumers Sign up to Green Electricity?" *Business Strategy and the Environment* 20 (1): 1–17.

Pannell, D. J., G. R. Marshall, N. Barr, A. Curtis, F. Vanclay, and R. Wilkinson. 2006. "Understanding and Promoting Adoption of Conservation Practices by Rural Landholders." *Australian Journal of Experimental Agriculture* 46 (11): 1407–1424.

Park, S. Y. 2009. "An Analysis of the Technology Acceptance Model in Understanding University Students' Behavioral Intention to Use E-Learning." *Educational Technology & Society* 12 (3): 150–162.

Park, S. Y., M. W. Nam, and S. B. Cha. 2012. "University Students' Behavioral Intention to Use Mobile Learning: Evaluating the Technology Acceptance Model." *British Journal of Educational Technology* 43 (4): 592–605.

Pei, Y., W. Xue, D. Li, J. Chang, and Y. Su. 2015. "Research on Customer Experience Model of B2C E-Commerce Enterprises Based on TAM Model." Paper presented at the 4th International Conference on Logistics, Informatics and Service Science, Springer Berlin Heidelberg.

Podsakoff, P. M., S. B. MacKenzie, J. Y. Lee, and N. P. Podsakoff. 2003. "Common Method Biases in Behavioral Research: A Critical Review of the Literature and Recommended Remedies." *Journal of Applied Psychology* 88 (5): 879.

Porumbescu, G. A. 2015. "Does Transparency Improve Citizens' Perceptions of Government Performance? Evidence from Seoul, South Korea." *Administration and Society*, 1–26. doi: 10.1177/0095399715593314.

Prieto, J. C. S., S. O. Migueláñez, and F. J. García-Peñalvo. 2014. "ICTs Integration in Education: Mobile Learning and the Technology Acceptance Model (TAM)." Paper presented at the Second International Conference on Technological Ecosystems for Enhancing Multiculturality. ACM.

Purnawirawan, N., P. De Pelsmacker, and N. Dens. 2012. "Balance and Sequence in Online Reviews: How Perceived Usefulness Affects Attitudes and Intentions." *Journal of Interactive Marketing* 26 (4): 244–255.

Raman, B. 2012. "The Rhetoric and Reality of Transparency: Transparent Information, Opaque City Spaces and the Empowerment Question." *The Journal of Community Informatics* 8 (2): 1–12.

Richardson, J. W. 2009. "Technology Adoption in Cambodia: Measuring Factors Impacting Adoption Rates." *Journal of International Development* 23 (5): 697–710.

Rijsdijk, S. A., and E. J. Hultink. 2003. "Honey, Have You Seen Our Hamster? Consumer Evaluations of Autonomous Domestic Products." *Journal of Product Innovation Management* 20 (3): 204–216.

Rogers, E. M. 2003. *Diffusion of Innovations*. 5th ed. New York, NY: The Free Press.

Rohunen, A., J. Markkula, M. Heikkila, and J. Heikkila. 2014. "Open Traffic Data for Future Service Innovation - Addressing the Privacy Challenges of Driving Data." *Journal of Theoretical and Applied Electronic Commerce Research* 9 (3): 71–89.

Sang, S., J.-D. Lee, and J. Lee. 2010. "E-Government Adoption in Cambodia: A Partial Least Squares Approach." *Transforming Government: People, Process and Policy* 4 (2): 138–157.

Santos, J. R. A. 1999. "Cronbach's Alpha: A Tool for Assessing the Reliability of Scales." *Journal of Extension* 37 (2): 1–14.

Schierz, P. G., O. Oliver Schilke, and B. W. Wirtz. 2010. "Understanding Consumer Acceptance of Mobile Payment Services: An Empirical Analysis." *Electronic Commerce Research and Applications* 9 (3): 209–216.

Shadbolt, N., K. O'Hara, T. Berners-Lee, N. Gibbins, H. Glaser, and W. Hall. 2012. "Linked Open Government Data: Lessons from data. gov. uk." *IEEE Intelligent Systems* 27 (3): 16–24.

Shih, H. P. 2008. "Continued Use of a Chinese Online Portal: An Empirical Study." *Behaviour and Information Technology* 27 (3): 201–209.

Shih, Y.-Y., and K. Fang. 2004. "The Use of a Decomposed Theory of Planned Behavior to Study Internet Banking in Taiwan." *Internet Research* 14 (3): 213–223.

Shin, D.-H. 2010. "MVNO Services: Policy Implications for Promoting MVNO Diffusion." *Telecommunications Policy* 34 (10): 616–632.

Sivarajah, U., Z. Irani, and V. Weerakkody. 2015. "Evaluating the Use and Impact of Web 2.0 Technologies in Local Government." *Government Information Quarterly* 32 (4): 473–487.

Steiger, J. H. 2007. "Understanding the Limitations of Global Fit Assessment in Structural Equation Modelling." *Personality and Individual Differences* 42 (5): 893–898.

Stevens, J. 1996. *Applied Multivariate Statistics for the Social Sciences*. Mahwah, NJ: Lawrence Erlbaurn Associates.

Straub, D., D. Gefen, and M.-C. Boudreau. 2004. "The ISWorld Quantitative, Positivist Research Methods Website." Accessed April 29, 2013. http://home.aisnet.org/displaycommon.cfm?an=1&subarticlenbr=495

Sundarraj, R. P., and N. Manochehri. 2013. "Application of an Extended TAM Model for Online Banking Adoption: A Study at a Gulf Region University." In *Managing Information Resources and Technology: Emerging Applications and Theories: Emerging Applications and Theories*, edited by M. Khosrow-Pour, 2–13. Hershey, PA: Information Science Reference.

Surowiecki, J. 2004. *The Wisdom of Crowds: Why the Many Are Smarter than the Few and How Collective Wisdom Shapes Business Economies, Societies and Nations*. New York, NY: Doubleday.

Tabachnick, B. G., and L. S. Fidell. 2007. *Using Multivariate Statistics*. 5th ed. New York, NY: Allyn and Bacon.

Teo, T. S. H., and S. H. Pok. 2003. "Adoption of WAP-Enabled Mobile Phones among Internet Users." *Omega* 31 (6): 483–498.

Tornatzky, L. G., and K. J. Klein. 1982. "Innovation Characteristics and Innovation Adoption-Implementation: A Meta-Analysis of Findings." *IEEE Transactions on Engineering Management* 29 (1): 28–45.

Ubaldi, B. 2013. "Open Government Data: Towards Empirical Analysis of Open Government Data Initiatives." OECD Working Papers on Public Governance, No. 22. Paris: OECD Publishing. doi: 10.1787/5k46bj4f03s7-en.

van Veenstra, A. F., and T. A. van den Broek. 2013. "Opening Moves. Drivers, Enablers and Barriers of Open Data in a Semi-Public Organization." Paper presented at the 12th Electronic Government Conference, Koblenz, Germany.

Venkatesh, V., M. G. Morris, G. B. Davis, and F. D. Davis. 2003. "User Acceptance of Information Technology: Toward a Unified View." *MIS Quarterly* 27 (3): 425–478.

Wang, J., and S. Senecal. 2007. "Measuring Perceived Website Usability." *Journal of Internet Commerce* 6 (4): 97–112.

Wangpipatwong, S., W. Chutimaskul, and B. Papasratorn. 2008. "Understanding Citizen's Continuance Intention to Use E-Government Website: A Composite View of Technology Acceptance Model and Computer Self-Efficacy." *The Electronic Journal of E-Government* 6 (1): 55–64.

Zhang, L., J. Zhu, and Q. Liu. 2012. "A Meta-Analysis of Mobile Commerce Adoption and the Moderating Effect of Culture." *Computers in Human Behavior* 28 (5): 1902–1911.

Zuiderwijk, A., and M. Janssen. 2014a. "Barriers and Development Directions for the Publication and Usage of Open Data: A Socio-technical View." *Opportunities and Challenges for Public Governance* 4 (1): 115–135.

Zuiderwijk, A., and M. Janssen. 2014b. "Open Data Policies, Their Implementation and Impact: A Framework for Comparison." *Government Information Quarterly* 31 (1): 17–29.

Zuiderwijk, A., M. Janssen, S. Choenni, R. Meijer, and R. S. Alibaks. 2012. "Socio-Technical Impediments of Open Data." *Electronic Journal of E-Government* 10 (2): 156–172.

Zuiderwijk, A., M. Janssen, and Y. K. Dwivedi. 2015. "Acceptance and Use Predictors of Open Data Technologies: Drawing upon the Unified Theory of Acceptance and Use of Technology." *Government Information Quarterly* 32 (4): 429–440.

Appendix 1. Shortlisted constructs and sources

Constructs	Source(s)
Behavioural intention	Karahanna, Straub, and Chervany (1999), Teo and Pok (2003), and Shih and Fang (2004)
Perceived usefulness	Moore and Benbasat (1991), Shih (2008), and Hsu, Lu, and Hsu (2007)
Perceived ease of use	Moore and Benbasat (1991), Shih and Fang (2004), Chen 2008, Richardson (2009), and Sang, Lee, and Lee 2010
Social approval	Mallat et al. 2006, Dwivedi and Irani (2009), Claudy, Michelsen, and O'Driscoll (2011), and Ozaki (2011)

Appendix 2. Likert scale items

BI1: I plan to use open data, as the central idea of open data is to create transparency within a democracy
☐ Extremely Disagree ☐ Disagree ☐ Slightly Disagree ☐ Neutral ☐ Slightly Agree ☐ Agree ☐ Extremely Agree

BI2: Despite the known benefits of open data, my personal willingness to use open data is not high
☐ Extremely Disagree ☐ Disagree ☐ Slightly Disagree ☐ Neutral ☐ Slightly Agree ☐ Agree ☐ Extremely Agree

BI3: My willingness to use open data is not very high
☐ Extremely Disagree ☐ Disagree ☐ Slightly Disagree ☐ Neutral ☐ Slightly Agree ☐ Agree ☐ Extremely Agree

PU1: I find open data useful in making day-to-day decisions
☐ Extremely Disagree ☐ Disagree ☐ Slightly Disagree ☐ Neutral ☐ Slightly Agree ☐ Agree ☐ Extremely Agree

PU2: Using open data helps me make better decisions
☐ Extremely Disagree ☐ Disagree ☐ Slightly Disagree ☐ Neutral ☐ Slightly Agree ☐ Agree ☐ Extremely Agree

PU3: Open data helps me better understand government actions that directly affect me as a citizen
☐ Extremely Disagree ☐ Disagree ☐ Slightly Disagree ☐ Neutral ☐ Slightly Agree ☐ Agree ☐ Extremely Agree

PEOU1: Open data will be easy to use for me
☐ Extremely Disagree ☐ Disagree ☐ Slightly Disagree ☐ Neutral ☐ Slightly Agree ☐ Agree ☐ Extremely Agree

PEOU2: I believe that using open data websites is challenging and frustrating
☐ Extremely Disagree ☐ Disagree ☐ Slightly Disagree ☐ Neutral ☐ Slightly Agree ☐ Agree ☐ Extremely Agree

PEOU3: My understanding of open data is very clear
☐ Extremely Disagree ☐ Disagree ☐ Slightly Disagree ☐ Neutral ☐ Slightly Agree ☐ Agree ☐ Extremely Agree

SA1: People important to me think I should use open data
☐ Extremely Disagree ☐ Disagree ☐ Slightly Disagree ☐ Neutral ☐ Slightly Agree ☐ Agree ☐ Extremely Agree

SA2: My family, friends & colleagues support the use open data
☐ Extremely Disagree ☐ Disagree ☐ Slightly Disagree ☐ Neutral ☐ Slightly Agree ☐ Agree ☐ Extremely Agree

SA3: People who influence my behavior think I should use open data
☐ Extremely Disagree ☐ Disagree ☐ Slightly Disagree ☐ Neutral ☐ Slightly Agree ☐ Agree ☐ Extremely Agree